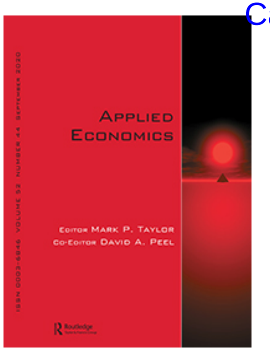
EXHIBIT B



Routledge
Taylor & Francis Group

Applied Economics

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/raec20

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To cite this article: Mohammad Hashemi Joo, Yuka Nishikawa & Krishnan Dandapani (2020) Announcement effects in the cryptocurrency market, Applied Economics, 52:44, 4794-4808, DOI: 10.1080/00036846.2020.1745747

To link to this article: https://doi.org/10.1080/00036846.2020.1745747

APPLIED ECONOMICS
2020, VOL. 52, NO. 44, 4794–4808
https://doi.org/10.1080/00036846.2020.1745747

Announcement effects in the cryptocurrency market

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ABSTRACT

Cryptocurrencies have gained popularity as new economic investment assets globally in recent years. This study examines market reactions to major news events associated with cryptocurrencies. Abnormal returns as well as cumulative abnormal returns (CARs) around major news announcements, both positive and negative, are investigated for three primary cryptocurrencies: Bitcoin, Ethereum, and Ripple. High abnormal returns are observed on the event day (Day 0), and CARs typically diverge during event windows of (−3, 6) and (0, 6), indicating that the information is not fully reflected in prices immediately after the news events. The CARs that linger for six days after an event suggest that the information flow in the cryptocurrency market is visibly slow. The magnitudes of CARs are larger for negative events than for positive events, implying that the market reaction to negative events is stronger than to positive announcements. The findings of this study may have crucial implications for investors, arbitragers and practitioners as we document evidence of potential trading opportunities for investors who initiate a trading position even after announcements.

KEYWORDS

Cryptocurrency; event study; trading opportunities; abnormal returns

JEL CLASSIFICATION

E42; G14

I. Introduction

Cryptocurrencies, among which Bitcoin has been the largest by market capitalization, have become a mainstream investment asset in recent years. There are 2,424 different cryptocurrencies on the market as of February 2020 (coinmarketcap.com), and this number is still increasing. The aims of this study are twofold. First, we examine market reactions during major event announcement periods using event study methodology. Second, we further investigate if the information diffusion allows arbitragers to have an opportunity to make positive profits even after the event announcement. While the literature presents mixed views on the informational efficiency of the cryptocurrency market, this article attempts to find evidence of potential profitable trading opportunities even a few days after an event announcement. To the best of our knowledge, this study is the first to document trading opportunities for an investor to make a profit in the cryptocurrency market even when he/she places a trade after the news becomes public. As a result, this study has crucial implications for progressive investment strategies used by investors and practitioners who are already in the market as well as those who are willing to participate in the cryptocurrency market. These opportunities persist even after making robust adjustments incorporating trading costs.

Among several of their key findings, Ciaian, Rajcaniova, and Kancs (2016) present that the arrival of new information has a positive effect on Bitcoin price. In addition, numerous studies support speculative aspects of cryptocurrencies (for example, Dwyer 2015; Böhme et al. 2015). Some of these articles entertain the idea that cryptocurrency prices appear to be set mainly by market sentiments (Dowd 2014; Weber 2016). Motivated by these findings, we examine market reactions to major event announcements associated with cryptocurrencies by computing abnormal returns as well as cumulative abnormal returns (CARs) around such events. We focus on the three largest cryptocurrencies by market capitalization: Bitcoin, Ethereum, and Ripple. Ten positive and 10 negative major news announcements for each of the three currencies are collected from various online news outlets. There has been an unsettled debate on whether cryptocurrency should be categorized as a commodity,

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currency, or security with different regulators and countries applying different metrics. To move away from such a debate, and due to the unavailability of a reliable proxy for market returns such as a market index (S&P 500 for the stock market, for example) in the cryptocurrency market, we apply the mean-adjusted returns model. In this model, the mean return of the previous trading days is employed as the baseline-expected return, and abnormal returns are calculated as the difference between the actual daily return and the expected return. Cumulative abnormal returns are calculated by summing the abnormal returns during the event window. We use the event windows of Day −3 through Day 6 and Day 0 to Day 6 as baseline windows. Nonparametric test procedures proposed by Corrado (1989) as well as Kolari and Pynnonen (2011) are applied to obtain t-statistics as the sample is found not to be normally distributed. Our results show high abnormal returns on the event day (Day 0) and CARs that typically diverge during the event windows of (−3, 6) and (0, 6), indicating that the information is not fully reflected in prices immediately after the events. CARs that remain for six days after an event imply that investors may be able to take advantage of the slow information flow to make profits by entering the market even after the announcement of the events. The larger magnitudes of CARs observed for negative events than for positive events suggest that the market reaction to negative events is stronger than to positive events. As robustness tests, we utilize different time frames, 180 days and 60 days compared to 365 days used in the baseline analysis, to compute the expected return because of the extreme volatility experienced in the market from the end of 2017 to the beginning of 2018. Our baseline results are robust with expected returns computed based on mean values using different time frames. We further confirm the validity of our findings by presenting out-of-sample analysis in which the trading strategies utilizing our findings are found to be profitable during the period examined.

The rest of the article is organized as follows. Section 2 briefly reviews the literature on the cryptocurrency market and cryptocurrency prices. Section 3 presents the data and methodology. Section 4 discusses the main findings. Lastly, Section 5 offers concluding remarks.

II. Literature review

One of the most fundamental questions about a financial market is whether the market is efficient (Fama 1970, 1998). The first study on the informational efficiency of cryptocurrencies is done by Urquhart (2016) using Bitcoin data. The study concludes that the Bitcoin market is generally inefficient. Nadarajah and Chu (2017) test the market efficiency not on daily returns but on an odd integer power of daily returns without suffering from any loss of information and find that power transformed Bitcoin returns can satisfy the efficient market hypothesis. Bariviera (2017) studies the dynamics of long-range dependence properties of Bitcoin returns from 2011 to 2017 using the Hurst exponent and finds evidence of the time-varying behaviour of market efficiency. Tiwari et al. (2018) further test the informational efficiency of Bitcoin from July 2010 to June 2017 by employing a set of robust long-range dependence estimators and present evidence of Bitcoin market efficiency. Using high-frequency data, Zargar and Kumar (2019) provide evidence of informational inefficiency at higher frequency levels. In tests of weak-form market efficiency of intraday Bitcoin prices, Sensoy (2019) finds a trend of Bitcoin markets becoming more informationally efficient. Kristoufek (2018) examines Bitcoin market efficiency using data from two markets as to the US dollar and Chinese yuan and finds both markets being mostly inefficient from 2010 to 2017. Kristoufek and Vosvrda (2013) present strong evidence of inefficiency for most of the sample period of 2010 to 2017. Cheah et al. (2018) show moderate to high inefficiency in Bitcoin markets, suggesting the possibility for investors to capture speculative profits.

The market efficiency of Bitcoin has been thoroughly explored using different approaches, only resulting in inconclusive outcomes, necessitating the need for examination of the efficiency of other cryptocurrencies. Zhang et al. (2018b) examine nine different cryptocurrencies and find that all of these cryptocurrencies show market inefficiency. Greatly extending the sample, Wei (2018) tests 456 cryptocurrencies and concludes that the

market efficiency of established cryptocurrencies is improving.

Some researchers bring psychological aspects to justify sharp movements in market prices. For example, DeBondt and Thaler (1985) find that investors in the stock market overreact to unexpected and dramatic news. They discover substantial weak form market inefficiencies in the stock market. In the cryptocurrency market, Chevapatrakul and Mascia (2019) find some evidence of overreaction in the Bitcoin market during days of sharp price declines and during weeks of market rallies.

Hodoshima and Otsuki (2019) assess Bitcoin performance using the Aumann and Serrano performance index and Sharpe ratio compared to the performance of other assets. Zhang et al. (2018a) study stylized facts (important statistical properties) of random variations in prices of eight different cryptocurrencies. Wang et al. (2019) investigate the predictive power of Bitcoin volatility forecasts of the ARJI, GARCH, EGARCH, and CGARCH models. Tiwari, Kumar, and Pathak (2019) test a number of GARCH and stochastic volatility models to find the best model to capture the dynamics of Bitcoin and Litecoin pricing. They also find evidence in the leverage effect that cryptocurrencies do not behave comparably to stock prices. Using an extreme-value-theory-based method, Feng, Wang, and Zhang (2018) analyse the extreme characteristics (tail risk) of seven cryptocurrencies. Among all, the study by Bouri et al. (2018) has the most practical implications for investors and fund managers. They examine return and volatility spillovers between Bitcoin and four asset classes in bear and bull market conditions up to October 2017 and find that the Bitcoin market is not completely isolated from other markets as its returns are correlated to returns of other assets, especially commodities. In addition, they find evidence that Bitcoin collects more volatility than it transmits to other markets.

Irrespective of the nature of cryptocurrencies, in an academic sense, we can use event study methodology to examine market reactions to announcements. Studies such as Brown and Warner (1985) report that the increase in variance may result in misspecification of traditional test statistics. The typical conclusion in event studies conducted on daily data is that, on average, stock prices seem to adjust within a day of event announcements. Although prices on average adjust quickly to firm-specific information, a common finding in event studies is that the dispersion of returns increases around information events.

Event study methodology is also applied by Park (2004), to multiple countries. The findings show that the use of the single country market model in a multi-country event study is likely to overestimate changes in firm value, demonstrating the need for a world market model. In a notable study, Kwok and Brooks (1990) apply event study methodology to the foreign exchange market with different conditions in the choice of foreign currency or numeraire, level of abnormal shock, sample size, length of estimation period, market return proxy, and time period examined. The results underscore some of the challenges when event study methodology is applied to the field of foreign exchanges.

Our article makes two primary contributions. First, we attempt to explore reactions of the cryptocurrency market to positive and negative events utilizing event study methodology. Second, we identify the possible profit-making opportunities based on the speed of information flow. This has significant implications for trading strategies that can be used by arbitragers, investors and practitioners. The objective of this article is to provide evidence of potential positive trading opportunities in the market. Our findings can be supported by the findings of the market inefficiency documented in several prior studies.

III. Data and methodology

Sample

In this study, we focus on the three largest cryptocurrencies by market capitalization: Bitcoin, Ethereum, and Ripple. These currencies have ample liquidity, are traded on multiple exchanges with substantial trading volume, and have a global market. As of February 2020, Bitcoin has a market cap of 175 USD billion representing about 64% of the total cryptocurrency market, followed by Ethereum with a market cap of 29 USD billion representing about 11% of the total market, and Ripple with a market cap of 12 USD billion

representing approximately 4% of the total market. These three currencies represent approximately 80% of the market capitalization of the total cryptocurrency market, which has a market value of 275 USD billion. Historical daily pricing data on Bitcoin, Ethereum, and Ripple are obtained from the website finance.yahoo.com, which provides long histories of various cryptocurrency exchange rates against the U.S. Dollar (USD). To be consistent in our comparison, daily prices are taken at close in the British Standard Time.

Following the literature, the daily returns are calculated by taking the first difference in the logarithm of daily closing exchange rates:

$$R_t = \ln(P_t) - ln(P_{t-1})$$

Since no reliable proxy for the market such as a market index (S&P 500 for the stock market, for example) has been established in the cryptocurrency market, we use the mean-adjusted returns model in this study. Whereas we also considered an option of constructing a cryptocurrency market index of our own, it may not be feasible to come up with a practical index due to limited data availability. In addition, this approach may not work for Bitcoin since it dominates the market. Using the mean of the last year (365 trading days for exchange rates) as the expected return, the abnormal return is calculated as the difference between the actual daily return and the expected return. The CAR is calculated by summing the abnormal returns during the event window. We use the event windows of Day −3 through Day 6 and Day 0 to Day 6. In the case of analysing global markets, there may not be an immediate diffusion effect when changes are proposed (e.g. Park 2004). Time zone, trading zone, cultural as well as language differences, and liquidity issues in cryptocurrency markets may necessitate considering an event window beginning even before Day −1, a window typically used in finance literature when studies are conducted in one country.[1] The use of the event window ending in Day 6 is determined by the fact that the CARs continue to increase until Day 6. This is also to investigate if there is any trade opportunity for an investor who enters the market after the news comes out (i.e. becomes public information).[2]

The event day (Day 0) is defined as the day in which the news event occurs. Since we use the 365-day average, the events considered in this study are taken one year after the beginning of our sample period. With this, the events are chosen from the time period of 1 January 2015 to 31 October 2018 for Bitcoin; 5 August 2016, to 31 October 2018 for Ethereum; and 31 January 2016, to 31 October 2018 for Ripple.

Selection of major events

In this article, major news announcements are categorized as positive or negative events. Positive events are defined as those events that are predicted to bring an expansionary effect to the cryptocurrency market, and therefore we should expect a positive return from those events. Similarly, negative events are defined as those events that are expected to bring a contractionary effect to the cryptocurrency market, and therefore we should expect a negative return from those events. Below we summarize examples of positive and negative events based on their nature/types.

Positive Events:

- Regulation: Main regulation events are national regulation changes in one of the countries with a high volume of digital currency trading. Depending on the context of the regulation, a regulation event can have positive impacts. For example, the news of Japan's declaration of Bitcoin as a legal tender is considered a positive event as it has an expansionary effect bringing in more traders.
- Exchange: Exchange-related news can be a positive event. One of the main exchange news events is the launch of Bitcoin futures on the two major exchanges, the Chicago Mercantile Exchange (CME) and the Chicago Board Options Exchange (CBOE). News about a new exchange being established is also categorized as an exchange news event. One example of this is that Coinbase launched a U.S. licenced exchange on 26 January 2016. Exchange-related

[1]To validate this point, we also used event windows of (−2, 6) and (−1, 6) and found similar results. Such findings are not included in this paper for brevity.
[2]We also used shorter windows such as (−3, 3) and (0, 3) as robustness checks, and the CAR patterns still hold with similar results.

news is usually considered positive because it indicates the expansion and availability of enhanced trading possibilities.

- Split: News on currency splits or forks is normally a significant event in the cryptocurrency market as it enhances liquidity and enables the micro-structure needs of participants. One of the key examples of split news is the news on the first hard fork of Bitcoin into Bitcoin and Bitcoin Cash on 1 August 2017. The news came out several days earlier, on 22 July 2017. In most cases, split news can be considered positive because the reason for splits or forks is usually to upgrade a system.
- Partnership: Events under this category are news reports about new partnerships between large organizations. One example of this is the Ripple partnership announcement with MoneyGram on 11 January 2018. Partnership news is generally perceived as a positive event as it enhances the global platform of trading and brings in more players who can benchmark and leverage the existing technology for enhanced product offerings.

Negative Events:

- Hacking: There have been quite a few large, high-profile cryptocurrency hacks over the last few years. Millions of dollars are reported stolen every time a digital currency exchange gets hacked. While the underlying blockchain technology is fundamentally more secure than centralized database systems, the ecosystem is still new, and poor programming practices create various security vulnerabilities, especially with systems built around blockchains. News of hacking is perceived as a negative event since hacking of an exchange would directly affect the investors' confidence who trade at the hacked exchange with their assets directly exposed to the risk of being stolen. In addition, other potential investors in the market perceive it as riskiness of the whole digital currency system, since the vulnerability of the hacked exchange may be perceived as a proxy to represent the vulnerability of the market as a whole. Examples of high-profile hacking events include the hacking of the Bitfinex Exchange that took place on 2 August 2016. This hacking caused 120,000 units of Bitcoin, valued at 72 USD million at the time, to be stolen.
- Regulation: Regulation-related events constraining trading and investing can have negative impacts on the market depending on the context. For example, China's ban on cryptocurrencies is considered a negative event. While regulation news can be positive or negative, it is easy to distinguish based on the context of the regulation.
- Split: In some cases, news on splits or hard forks can have a negative impact on a specific cryptocurrency if it is a hard fork from the specific currency. Split news on one cryptocurrency can have a negative effect on other currencies that need an upgrade on the system but have not been upgraded for a while.
- Others: This category also includes news about comments made by significant market leaders in the financial or regulatory industry. While events in this category could have either a positive or a negative impact, it is typically apparent how the market will react to the news. For example, news on bad comments made by a well-known market-maker or regulatory authority should bring negative movement in the market.

We collect the major news events on Bitcoin, Ethereum, and Ripple from numerous online sources including but not limited to CNBC, Forbes, NY Times, Coindesk, CCN, and Cointelegraph. The dates of the news events are recorded in U.S. Eastern Time. For each digital currency, 10 news announcements we consider as the largest with a positive impact on the market and another 10 news announcements we consider as the largest with a negative impact are selected as major events. Table 1 lists all major events (10 positive and 10 negative) selected for Bitcoin, Ethereum, and Ripple. They are categorized as Positive/Negative indicating the expected direction of the impact on the market. The table also lists five different event types: Regulation, Exchange, Hacking, Split, and Others with brief descriptions of the events.

Normality and nonparametric tests

Most event studies have relied on parametric test statistics. Implicit in this parametric testing is the

Table 1. List of major events: Bitcoin, Ethereum, and Ripple.

Date	Positive/Negative	Type of News	Event
Bitcoin			
4 January 2015	Negative	HACK	Bitstamp hacked
26 January 2015	Positive	EXCHANGE	Coinbase launches US licenced exchange
22 October 2015	Positive	REGULATION	EU declares no VAT (value-added-tax) on Bitcoin trades
3 November 2015	Positive	PARTNERSHIP	Bitcoin Sign accepted into Unicode
14 January 2016	Negative	OTHERS	Mike Hearn, an ex-Google developer, declares Bitcoin had failed
2 August 2016	Negative	HACK	Bitfinex hacked
10 March 2017	Negative	REGULATION	SEC denies Winkelvoss ETF
1 April 2017	Positive	REGULATION	Japan declares Bitcoin as legal tender
22 July 2017	Positive	SPLIT	The first hard fork of Bitcoin happened on 1 August 2017, resulting in the creation of Bitcoin Cash
3 August 2017	Positive	EXCHANGE	CBOE plans to launch Bitcoin futures
3 September 2017	Negative	REGULATION	China bans companies from raising money through ICOs
31 October 2017	Positive	EXCHANGE	CME announces to launch Bitcoin futures
8 November 2017	Negative	SPLIT	SegWit2X cancelled
1 December 2017	Positive	EXCHANGE	CME, CBOE to begin Bitcoin futures trading
19 December 2017	Negative	EXCHANGE	Top cryptocurrency marketplace starts supporting rival bitcoin cash
29 January 2018	Negative	REGULATION	New cryptocurrency rules just came into effect in South Korea
7 March 2018	Negative	HACK	Binance detects unauthorized transactions
10 June 2018	Negative	HACK	Korea's Coinrail hacked
2 July 2018	Positive	EXCHANGE	Coinbase launches crypto custody service for institutional investors
15 October 2018	Positive	PARTNERSHIP	Fidelity launches trade execution and custody for cryptocurrencies
			(cont'd.)
Ethereum			
23 January 2017	Negative	OTHERS	Proposed 'Ethereum' investment vehicle sparks controversy
13 February 2017	Positive	PARTNERSHIP	JP Morgan, Santander said to join New Ethereum Blockchain Group
28 February 2017	Positive	PARTNERSHIP	Big Corporates (JP Morgan, Microsoft, BP and Wipro, etc.) unite for launch of Enterprise Ethereum Alliance
26 April 2017	Positive	PARTNERSHIP	Former Coinbase engineer launches Ethereum search engine
22 May 2017	Positive	PARTNERSHIP	Deloitte joins Blockchain Consortiums Ethereum Alliance and Hyperledger
5 June 2017	Positive	PARTNERSHIP	Vladimir Putin and Vitalik Buterin discuss Ethereum 'opportunities'
17 June2017	Negative	HACK	The DAO attacked: Code issue leads to $60 million Ether theft
25 June 2017	Negative	OTHERS	Fake news of a fatal car crash of Vitalik Buterin wiped out $4 billion in Ethereum's market value
3 August 2017	Positive	EXCHANGE	CBOE plans to launch Bitcoin futures
3 September 2017	Negative	REGULATION	China bans companies from raising money through ICOs
15 September 2017	Negative	REGULATION	China shuts down all Bitcoin and cryptocurrency exchanges
21 November 2017	Positive	OTHERS	Ethereum startup ConsenSys opens new London Office
11 December 2017	Positive	EXCHANGE	CBOE Bitcoin futures are launched
29 January 2018	Negative	REGULATION	New cryptocurrency rules come into effect in South Korea
8 February 2018	Negative	HACK	BitGrail hacked
14 March 2018	Negative	OTHERS	Google bans all cryptocurrency-related advertising
10 June 2018	Negative	HACK	Korea's Coinrail hacked
20 June 2018	Negative	HACK	Korea's Bithumb hacked
2 July 2018	Positive	EXCHANGE	Coinbase launches crypto custody service for institutional investors
15 October 2018	Positive	PARTNERSHIP	Fidelity launches trade execution and custody for cryptocurrencies
			(cont'd.)
Ripple			
13 June 2016	Positive	PARTNERSHIP	Ripple receives New York's first BitLicense for an institutional use case of digital assets
2 August 2016	Negative	HACK	Bitfinex hacked and $60 million stolen
23 September 2016	Positive	PARTNERSHIP	Announcement of Ripple's global payments steering group
1 November 2016	Positive	REGULATION	Japan rises to Blockchain challenge with new consortium
2 March 2017	Positive	PARTNERSHIP	47 banks complete DLT cloud pilot with Ripple Tech
10 March 2017	Negative	REGULATION	SEC denies Winkelvoss ETF
1 April 2017	Positive	REGULATION	Japan declares Bitcoin as legal tender
17 June 2017	Negative	HACK	The DAO attacked: code issue leads to $60 million Ether theft
3 August 2017	Positive	EXCHANGE	CBOE plans to launch Bitcoin futures
3 September 2017	Negative	REGULATION	China bans companies from raising money through ICOs
15 September 2017	Negative	REGULATION	China shuts down all Bitcoin and cryptocurrency exchanges
16 November 2017	Positive	PARTNERSHIP	American Express opens first Blockchain corridor with Ripple Tech
11 December 2017	Positive	EXCHANGE	CBOE Bitcoin futures are launched
26 January 2018	Negative	HACK	Japanese cryptocurrency exchange loses more than $500 million to hackers
2 February 2018	Negative	OTHERS	J.P. Morgan Chase, Bank of America and Citigroup announce decision not to allow customers to buy cryptocurrencies with the companies' credit card
7 March 2018	Negative	HACK	Binance detects unauthorized transactions
10 June 2018	Negative	HACK	Korea's Coinrail hacked
20 June 2018	Negative	HACK	Korea's Bithumb hacked
2 July 2018	Positive	EXCHANGE	Coinbase launches crypto custody service for institutional investors
15 October 2018	Positive	PARTNERSHIP	Fidelity launches trade execution and custody for cryptocurrencies

Table 1 presents the major news events for the three largest cryptocurrencies, Bitcoin, Ethereum, and Ripple, from January 2015 to 31 October2018. Panel A summarizes the major events for Bitcoin, Panel B summarizes the major events for Ethereum and Panel C for Ripple.

assumption of normality of the probability of distribution of returns. Corrado's early work in 1989 shows that in simulations with daily security-return data, the nonparametric rank test outperforms the parametric t-test. The rank test does not require symmetry in cross-sectional return distributions for the correct specification. In further study, Corrado and Zivney (1992) document that the performance of the sign test is dominated by the performance of the rank test. The correct specification of the sign test requires equal numbers of positive and negative abnormal returns. Kolari and Pynnonen (2011) advance the sign test further. They argue that when stock prices are not normally distributed, the power of nonparametric tests in event study analyses dominates the power of parametric tests. When applied to multiple day analyses, the proposed generalized rank (GRANK) test can better calculate both one single day and CARs. This statistic is robust, and the GRANK procedure outperforms the rank tests of CARs as well as is robust to abnormal return serial correlation and event-induced volatility. The GRANK procedure exhibits a superior power relative to popular parametric tests.

In this study, first we conduct a normality test to determine if our sample is normally distributed by using the Shapiro–Wilk test. This test is commonly found to have a strong power for a given significance (e.g. Razali and Wah 2011). Once non-normality of the sample is verified, nonparametric test procedures are applied to obtain statistics of our analysis. We use the classic rank test introduced by Corrado (1989) for single-day abnormal returns and the GRANK test proposed by Kolari and Pynnonen (2011) for multiple-day CARs. These procedures are selected as the Corrado rank test and the Corrado-Zivney rank test is found to be significantly less effective when extended for multiple-day tests (Kolari and Pynnonen 2011).

IV. Event analysis results

Baseline results

Panel A of Table 2 presents the summary statistics of daily abnormal returns for each of three digital currencies from the whole sample period based on the 365-day moving average. The mean abnormal return of Bitcoin is positive while that of Ethereum is negative and that of Ripple is almost zero. The maximum and minimum returns of Bitcoin and Ethereum are similar to each other (maxima of 24.5% and 25.4%, and minima of −28.9% and −27.2%, respectively) while those of Ripple are much larger in magnitude with a maximum of 102.3% and a minimum of −65.7%. Also, Ripple has the largest coefficient of variation with an absolute value of 3037.51, compared to Bitcoin's 329.75 and Ethereum's 22.84. Based on the maximum and minimum values as well as coefficient of variation, Ripple is the most volatile asset among the three currencies for our sample period.

Panel B of Table 2 illustrates the results of our normality test using the Shapiro-Wilk procedure. The null-hypothesis of the Shapiro–Wilk test is normality in the population. The test results show that in all of the three cases, we cannot reject the

Table 2. Summary statistics and normality – daily abnormal returns.

Panel A. Summary Statistics

	N	Mean	Median	Std Dev	Coeff. of Variation	Max	Min	Skewness	Excess Kurtosis
Bitcoin	1,400	0.012%	0.093%	3.975%	329.75	24.471%	−28.931%	−0.470	6.693
Ethereum	817	−0.261%	−0.544%	5.961%	−22.84	25.435%	−27.183%	0.348	3.059
Ripple	1,005	−0.003%	−0.576%	8.490%	−3037.51	102.268%	−65.655%	2.518	30.436

Panel B. Shapiro–Wilk Normality Test

	N	*W*	*V*	*z*	*Prob>z*
Bitcoin	1,400	0.897	88.549	11.253	0.000
Ethereum	817	0.943	29.792	8.336	0.000
Ripple	1,005	0.756	154.37	12.482	0.000

Panel A of Table 2 summarizes the statistics of abnormal returns of Bitcoin, Ethereum, and Ripple. The daily abnormal returns are calculated using the 365-day average as the expected return. The time period used for Bitcoin is from 1 January 2015 to 31 October 2018. The time period used for Ethereum is from 5 August 2016 to 31 October 2018. The time period used for Ripple is from 31 January 2016 to 31 October 2018. *N* is the number of observations, *Median* is the median value, *Mean* is the average, and *Std Dev* is the standard deviation of the observations. *Coeff. of Variation* is the coefficient of variation values computed as standard deviation divided by mean. *Min* and *Max* are the minimum and maximum values of observations for each cryptocurrency in this study, respectively. *Skewness* and *Excess Kurtosis* are the skewness and excess kurtosis of the observations for each cryptocurrency, respectively. Panel B of this table presents the results from the Shapiro-Wilk normality test for Bitcoin, Ethereum, and Ripple. *N* is the number of observations, *W* and *V are* the W and V values specific to the Shapiro–Wilk test, respectively, and *z* is the z-statistic.

null hypothesis, indicating that our sample populations of Bitcoin, Ethereum and Ripple are not normally distributed.[3] These results validate the use of nonparametric tests over parametric tests. Therefore, the t-statistics of the following arguments are obtained from nonparametric tests.

Table 3 presents the average abnormal returns (AR) from Day −3 to Day 6 of events. The average values are calculated for each 10 positive events and each 10 negative events separately for the three cryptocurrencies in this study. In general, the ARs on the event announcement day are larger than the ARs in other days within the event window, as expected. The only exceptions are observed for the positive events for Ethereum and the negative events for Ripple. The positive events for Ethereum exhibit the highest average AR on Day −2. This may be reflecting the cases where the diffusion of rumours about upcoming positive news start coming around a few days before the actual announcement of the news. As for the negative events for Ripple, the largest AR is observed on Day 3. It is not clear if this is due to the fact that the market reaction is slower to negative news related to Ripple and the market response to the news starts picking up a few days after the event or if this is from a market reaction to another main event not considered in our sample.

Panel A of Table 4 summarizes the average CARs from Day −3 to Day 6 of events for positive and negative events of Bitcoin, Ethereum, and Ripple. Panel A of Figure 1 plots the event days on the x-axis and CARs on the y-axis. In general, the cumulative returns continue to increase in magnitude from Day −3 to Day 6 with a slight pullback on Day 2 for most cases. Among positive events, Ethereum has the highest CARs at Day 6 with a value of 29.37%, whereas Ripple has the highest CARs in magnitude among negative events at Day 6 with a value of −45.12%. Bitcoin exhibits the smallest CARs in both positive and negative events (15.87% and −17.83%, respectively). The overall observation is that the CARs for negative events are larger in magnitude compared to the CARs for positive events.

Panel B of Table 4 summarizes the average CARs from Day 0 to Day 6 for positive and negative events of Bitcoin, Ethereum, and Ripple. Panel B of Figure 1 plots the event days on the x-axis and CARs on the y-axis. Again, this event window is used to investigate if an investor can make any profit by placing a position in the market after the news becomes public information. In general, the cumulative returns continue to increase in magnitude from Day 0 to Day 6 although the increase in magnitude is not as much in some cases. The information given by the news is not fully reflected in the price right after the news announcement. This could create a trade opportunity for the investor to make a profit by taking advantage of this unpredictability. If the investor is aware that the return continues to increase for several days after the positive event, then he/she could make a profit by buying the currency right after the event occurs and sell it three to six days after the announcement.

One observation to point out is that the CARs for negative events are in general larger in magnitude compared to the CARs for positive events. For positive events, Ripple shows the largest CARs from Day 0 to Day 6. This implies that the market reaction to positive news related to Ripple is slower than the market reaction to positive news related to the other two assets. For negative events, Ripple exhibits the largest CARs from Day 3 to Day 6. This implies that the market reaction to negative news related to Ripple is slower than the market reaction to negative news related to the other two assets. In addition, the magnitude of CARs for Ripple negative events is significantly larger than any other CARs in this study. This implies that the market reacts to negative news related to Ripple more than it does to any type of news related to the other two currencies.

Robustness tests

As robustness tests, we utilize different time frames, 180 days and 60 days, to compute the expected return motivated by high volatility experienced in the cryptocurrency market. The market experienced extreme volatility for the period spanning from the end of 2017 to the beginning of 2018, which is part of our sample period. Panels A and B of Figure 2 plot the event days on the x-axis and CARs on the y-axis for the event windows of (−3, 6)

[3] Using the Shapiro-Francia procedure as well as a normality test based on skewness and another based on kurtosis, we also confirm the results from the Shapiro-Wilk procedure. The results from these tests are excluded for brevity.

Table 3. Average abnormal returns (ARs) around major events.

Bitcoin

	Positive Events				Negative Events			
Day	Average AR	Corrado t-stat	Skewness	Excess Kurtosis	Average AR	Corrado t-stat	Skewness	Excess Kurtosis
−3	1.27%	1.478	2.530	7.363	0.12%	−0.575	0.889	1.346
−2	1.10%	2.256	−0.896	−0.439	−1.43%	−2.612	1.351	2.820
−1	1.63%	2.216	0.829	2.166	−3.54%	−2.922	−1.394	2.369
0	3.33%	2.656	0.026	−1.794	−4.58%	−3.545	1.418	1.087
1	1.46%	2.633	−0.238	−0.407	−3.09%	−2.596	−0.969	−0.150
2	−1.30%	−0.503	−0.432	−1.047	−1.51%	−2.625	−0.067	−0.688
3	1.38%	1.949	1.742	3.399	−0.82%	−1.764	−0.838	2.805
4	2.68%	3.443	−0.622	−1.263	−1.37%	−2.324	−0.405	−0.573
5	3.18%	2.716	0.636	0.773	1.13%	−0.437	−0.394	0.156
6	1.13%	1.246	1.975	4.974	−2.74%	−2.689	−0.730	2.268

Ethereum

	Positive Events				Negative Events			
Day	Average AR	Corrado t-stat	Skewness	Excess Kurtosis	Average AR	Corrado t-stat	Skewness	Excess Kurtosis
−3	2.29%	3.171	1.692	4.478	−2.54%	−1.280	−1.313	0.275
−2	7.96%	2.243	0.522	−1.141	−4.31%	−1.622	−1.053	0.006
−1	3.70%	3.083	1.157	1.675	0.73%	−0.890	0.344	−0.957
0	0.74%	1.491	−0.242	2.126	−7.60%	−3.980	−0.114	−0.948
1	7.23%	2.979	−0.564	−1.057	1.04%	−1.640	−0.446	1.286
2	1.43%	1.097	0.563	0.207	1.45%	0.583	−1.066	1.620
3	3.74%	2.508	−0.398	−0.626	−7.35%	−3.557	−0.682	1.331
4	0.49%	0.615	2.170	5.122	−2.99%	−2.910	0.852	1.484
5	0.22%	1.424	1.195	2.446	−2.93%	−1.908	−0.130	−1.154
6	1.56%	1.979	0.254	0.341	−1.86%	−1.037	−0.840	0.533

Ripple

	Positive Events				Negative Events			
Day	Average AR	Corrado t-stat	Skewness	Excess Kurtosis	Average AR	Corrado t-stat	Skewness	Excess Kurtosis
−3	1.96%	2.541	1.116	0.821	−6.95%	−2.380	−0.850	0.571
−2	0.64%	1.506	−0.768	0.785	−5.48%	−3.325	−0.660	−2.802
−1	1.56%	2.898	0.593	−0.721	−1.61%	−2.770	−1.036	0.483
0	13.87%	3.160	0.065	−2.086	−7.67%	−3.638	0.394	1.575
1	2.79%	1.492	−0.929	−0.794	−1.40%	−1.152	−1.467	2.320
2	0.21%	0.376	1.276	1.811	0.86%	−0.833	−1.837	3.609
3	3.39%	1.280	0.203	−2.496	−11.10%	−3.006	−0.351	−2.963
4	1.37%	0.938	−1.063	−0.618	−4.40%	−2.138	0.979	1.726
5	5.24%	1.929	−1.031	0.947	−1.71%	−3.089	0.045	−2.028
6	−3.29%	−0.928	−0.523	−0.864	−5.66%	−2.193	−0.366	−2.742

Table 3 presents the average abnormal returns (ARs) around the event time. First, the daily abnormal returns are calculated for the days in the event window of (−3, 6) and (0, 6) for each event using the 365-day average as the expected return. After ARs are computed for all events, the average of those values from all events are taken for each cryptocurrency. T-statistics are also computed for each average AR using the Corrado (1989) rank test. *Skewness* and *Excess Kurtosis* are the skewness and kurtosis of 10 observations for each group, respectively.

and (0, 6), respectively, using the 180-day moving average as the expected return in computing the abnormal return. Figure 3 presents the same results as Figure 2 using the 60-day moving average. As illustrated in these figures, our baseline results are robust with the expected returns computed based on the mean values using different time frames of 180 days and 60 days.[4]

Out-of-sample analysis

To further examine the validity of our findings, we present out-of-sample analysis by demonstrating trading strategies utilizing our findings. We construct six different investment strategies that trade on out-of-sample events (after 1 November 2018) and test if these strategies can make profits. In the strategies that trade on positive news, investors

[4]T-statistics based on the Kolari and Pynnonen (2011) GRANK test are utilized to evaluate the statistical significance of the results using the 180-day moving average as well as the 60-day moving average, in the same way, we tested the statistical significance of the baseline results presented in Table 4.

Table 4. Average cumulative abnormal returns (CARs) around major events.

Panel A. Average Cumulative Abnormal Returns (CARs) for Event Window (−3, 6)

Bitcoin

	Positive Events				Negative Events			
Event Window	Average CAR	GRANK t-stat	Skewness	Excess Kurtosis	Average CAR	GRANK t-stat	Skewness	Excess Kurtosis
(−3,-3)	1.27%	−0.190	2.530	7.363	0.12%	−1.875	0.889	1.346
(−3,-2)	2.38%	1.518	−0.850	3.095	−1.32%	−1.545	0.519	−0.344
(−3,-1)	4.01%	1.730	−0.191	2.346	−4.86%	−2.504	−0.875	2.465
(−3,0)	7.34%	2.292	0.170	−1.252	−9.44%	−3.275	0.517	−1.456
(−3,1)	8.80%	2.951	−0.022	−0.850	−12.53%	−3.752	−1.103	2.873
(−3,2)	7.49%	3.214	−1.171	2.214	−14.04%	−4.467	0.100	−0.062
(−3,3)	8.87%	3.523	−1.457	2.623	−14.86%	−4.289	−0.514	−0.975
(−3,4)	11.56%	3.578	−1.140	0.980	−16.23%	−4.252	−0.200	−1.385
(−3,5)	14.74%	3.474	−0.620	0.789	−15.09%	−3.863	−0.784	0.023
(−3,6)	15.87%	3.770	1.764	4.688	−17.83%	−3.663	−1.568	3.269

Ethereum

	Positive Events				Negative Events			
Event Window	Average CAR	GRANK t-stat	Skewness	Excess Kurtosis	Average CAR	GRANK t-stat	Skewness	Excess Kurtosis
(−3,-3)	2.29%	2.862	1.692	4.478	−2.54%	0.315	−1.313	0.275
(−3,-2)	10.25%	3.138	1.614	3.104	−6.85%	−0.505	−1.319	1.876
(−3,-1)	13.95%	3.822	0.489	−1.817	−6.12%	−0.920	0.645	−1.518
(−3,0)	14.69%	3.912	0.058	−1.739	−13.72%	−2.007	0.250	−2.373
(−3,1)	21.92%	4.171	0.274	−1.266	−12.68%	−3.939	0.036	−2.087
(−3,2)	23.35%	4.066	0.051	−1.415	−11.23%	−3.713	−1.921	3.453
(−3,3)	27.10%	3.958	0.642	−0.619	−18.59%	−4.298	−2.126	5.049
(−3,4)	27.59%	3.909	−0.039	−1.083	−21.57%	−4.357	−0.925	1.040
(−3,5)	27.81%	3.907	−0.195	−1.172	−24.50%	−4.269	−0.878	1.366
(−3,6)	29.37%	3.896	−0.088	−1.602	−26.37%	−4.208	−0.025	−0.112

Ripple

	Positive Events				Negative Events			
Event Window	Average CAR	GRANK t-stat	Skewness	Excess Kurtosis	Average CAR	GRANK t-stat	Skewness	Excess Kurtosis
(−3,-3)	1.96%	2.388	1.116	0.821	−6.95%	−0.787	−0.850	0.571
(−3,-2)	2.60%	1.700	1.101	0.093	−12.43%	−1.472	0.401	0.250
(−3,-1)	4.15%	3.348	−1.201	1.113	−14.04%	−2.591	−0.783	1.233
(−3,0)	18.02%	4.085	0.809	−1.018	−21.71%	−3.215	−0.731	−0.029
(−3,1)	20.81%	4.432	2.077	4.425	−23.11%	−2.902	−1.426	2.514
(−3,2)	21.01%	4.302	2.172	4.773	−22.25%	−2.460	−1.724	3.362
(−3,3)	24.41%	4.104	1.963	4.084	−33.35%	−2.728	−1.422	1.319
(−3,4)	25.78%	4.076	1.898	3.814	−37.75%	−2.750	−0.821	−1.023
(−3,5)	31.02%	4.038	1.823	3.616	−39.46%	−2.996	−1.676	2.474
(−3,6)	27.73%	3.754	2.114	4.508	−45.12%	−2.888	0.224	−3.010

Panel B. Average Cumulative Abnormal Returns (CARs) for Event Window (0, 6)

Bitcoin

	Positive Events				Negative Events			
Event Window	Average CAR	GRANK t-stat	Skewness	Excess Kurtosis	Average CAR	GRANK t-stat	Skewness	Excess Kurtosis
(0,0)	3.33%	1.685	0.026	−1.794	−4.58%	−1.951	1.418	1.087
(0,1)	4.79%	2.531	−0.327	−0.874	−7.67%	−2.058	0.033	0.767
(0,2)	3.48%	1.987	−1.175	1.247	−9.18%	−1.850	0.272	−0.991
(0,3)	4.87%	2.721	−0.778	0.071	−10.00%	−2.068	−0.271	−0.166
(0,4)	7.55%	2.506	−1.209	0.277	−11.37%	−2.038	0.445	−0.266
(0,5)	10.73%	2.795	−0.603	−0.192	−10.23%	−2.091	−0.613	−0.089
(0,6)	11.86%	2.909	1.101	2.552	−12.97%	−2.411	−1.290	1.659

Ethereum

	Positive Events				Negative Events			
Event Window	Average CAR	GRANK t-stat	Skewness	Excess Kurtosis	Average CAR	GRANK t-stat	Skewness	Excess Kurtosis
(0,0)	0.74%	0.269	−0.242	2.126	−7.60%	−2.623	−0.114	−0.948
(0,1)	7.97%	1.762	1.079	0.663	−6.56%	−4.149	−0.774	−0.283
(0,2)	9.41%	1.992	−0.019	−0.766	−5.11%	−2.798	−0.132	−0.396
(0,3)	13.15%	2.034	0.833	0.933	−12.47%	−2.999	−1.068	0.834
(0,4)	13.64%	2.614	−0.092	−0.348	−15.45%	−4.163	−0.148	−1.473

(*Continued*)

Table 4. (Continued).

Panel B. Average Cumulative Abnormal Returns (CARs) for Event Window (0, 6)								
(0,5)	13.86%	3.175	0.118	−0.380	−18.38%	−5.395	−0.525	−0.938
(0,6)	15.43%	2.653	−0.229	0.472	−20.25%	−4.991	−0.624	−0.490
Ripple								
	Positive Events				Negative Events			
Event Window	Average CAR	GRANK t-stat	Skewness	Excess Kurtosis	Average CAR	GRANK t-stat	Skewness	Excess Kurtosis
(0,0)	13.87%	1.773	0.065	−2.086	−7.67%	−2.305	0.394	1.575
(0,1)	16.65%	2.379	1.417	2.105	−9.07%	−2.208	−1.525	2.622
(0,2)	16.86%	1.990	1.905	3.846	−8.21%	−1.673	−0.560	−3.045
(0,3)	20.25%	2.131	2.150	4.719	−19.31%	−2.337	−0.590	−3.223
(0,4)	21.62%	2.317	2.181	4.791	−23.71%	−3.060	−0.796	0.522
(0,5)	26.86%	2.278	1.584	3.378	−25.43%	−3.245	−0.507	−2.339
(0,6)	23.57%	2.035	2.046	4.329	−31.09%	−3.642	−0.692	−0.722

Table 4 presents the average cumulative abnormal returns (CARs) around the event time. First, the daily abnormal returns are calculated for the days in the event window of (−3, 6) and (0, 6) for each event using the 365-day average as the expected return. Then, the cumulative abnormal returns are computed for each event window of each currency. After all CARs are computed for all events, the average of those values from all events are taken for each cryptocurrency, and t-statistics are also computed for each average CAR using the generalized rank (GRANK) test proposed by Kolari and Pynnonen (2011). *Skewness* and *Excess Kurtosis* are the skewness and kurtosis of 10 observations for each group, respectively. Panel A presents the summary of CARs for the event windows of (−3, 6), and Panel B presents the summary of CARs for the event windows of (0, 6).

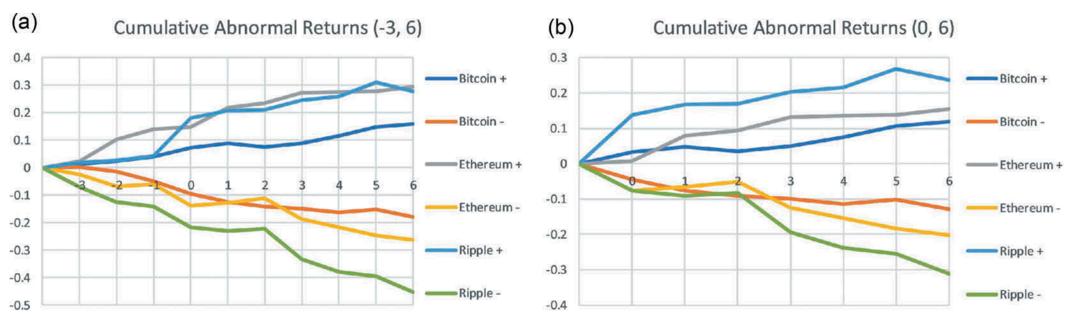

Figure 1. Average cumulative abnormal returns (CARs) around major events.

Figure 1 illustrates the movements of the average cumulative abnormal returns (CARs) around the event time for positive and negative events of each currency. Three hundred and sixty-five-day moving averages are used as the expected return in computing abnormal returns. Panel A exhibits the CAR movements for the event window of (−3, 6), and Panel B exhibits the CAR movements for the event window of (0, 6).Panel A. Movements of Average Cumulative Abnormal Returns (CARs) for Event Window (−3, 6). Panel B. Movements of Average Cumulative Abnormal Returns (CARs) for Event Window (0, 6).

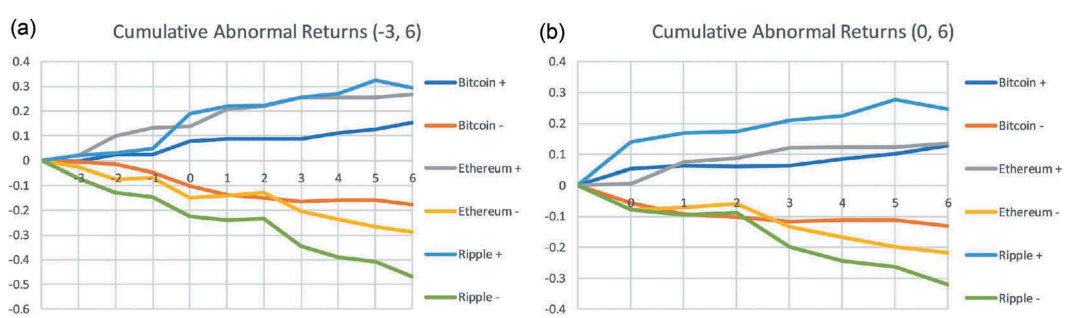

Figure 2. Average cumulative abnormal returns (CARs) around major events using 180-day average as expected return.

Figure 2 illustrates the movements of the average cumulative abnormal returns (CARs) around the event time for positive and negative events of each currency. One hundred and eighty-day moving averages are used as the expected return in computing abnormal returns. Panel A exhibits the CAR movements for the event window of (−3, 6), and Panel B exhibits the CAR movements for the event window of (0, 6).Panel A. Movements of Average Cumulative Abnormal Returns (CARs) for Event Window (−3, 6). Panel B. Movements of Average Cumulative Abnormal Returns (CARs) for Event Window (0, 6).

place a position in the market on Day 0 of the news event, hold the position for six days and close the position on Day 6. In the strategies that trade on negative news, investors short sell on Day 0 of the news event and buy back on Day 6. We assume 1.5% of each trading amount as the total

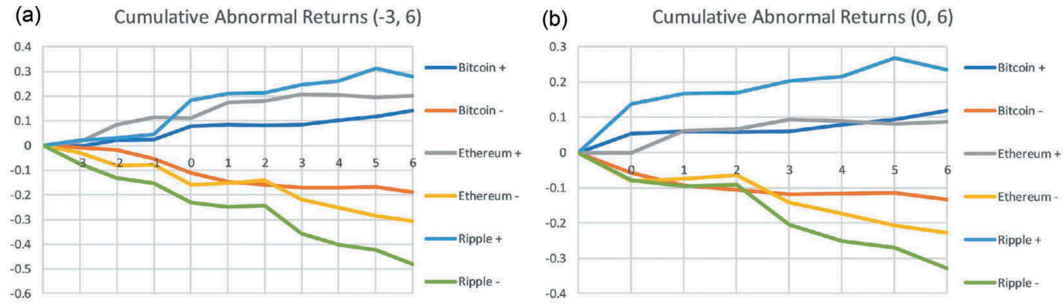

Figure 3. Average cumulative abnormal returns (CARs) around major events using 60-day average as expected return.

Figure 3 illustrates the movements of the average cumulative abnormal returns (CARs) around the event time for positive and negative events of each currency. Sixty-day moving averages are used as the expected return in computing abnormal returns. Panel A exhibits the CAR movements for the event window of (−3, 6), and Panel B exhibits the CAR movements for the event window of (0, 6).Panel A. Movements of Average Cumulative Abnormal Returns (CARs) for Event Window (−3, 6). Panel B. Movements of Average Cumulative Abnormal Returns (CARs) for Event Window (0, 6).

transaction cost accounting for exchange fees, network fees, and wallet fees. This value is based on the fees imposed by Coinbase.com, a digital currency exchange in the United States, in case funds are transferred from a U.S. bank or a Coinbase USD wallet. Potential transaction complications due to limited liquidity are ignored in this analysis as they have not been flagged as an issue recently at the actual exchanges.

Positive Event One: JP Morgan launches its own JPM Coin (14 February 2019)

Positive Event Two: Cryptocurrency wallet on WhatsApp set for release (25 March 2019)

Positive Event Three: Facebook announces Libra cryptocurrency (18 June 2019)

Negative Event One: Bitcoin Cash has a hard fork (13 November 2018)

Negative Event Two: Singaporean exchange Bitrue gets hacked (27 June 2019)

Negative Event Three: Federal Reserve Chairman Jerome Powell indicates concerns over Libra in his comments (10 July 2019)

Investor A: Trade 10,000 USD in Bitcoin based on positive news (buy, hold, and sell)

Investor B: Trade 10,000 USD in Ethereum based on positive news (buy, hold, and sell)

Investor C: Trade 10,000 USD in Ripple based on positive news (buy, hold, and sell)

Investor D: Trade 10,000 USD in Bitcoin based on negative news (short sell and buy back)

Investor E: Trade 10,000 USD in Ethereum based on negative news (short sell and buy back)

Investor F: Trade 10,000 USD in Ripple based on negative news (short sell and buy back)

The returns made by each of the investors are documented in Table 5. All investors in this analysis make positive profits by trading on the news events even after the news comes out, taking trading costs into consideration. This result confirms the validity of our baseline findings, and investors have opportunities to make positive returns by placing a position even after the information becomes publicly available.

One possible argument is that high returns made in these strategies can be due to the USD weakening against other currencies including cryptocurrencies, not due to the superior performance of each cryptocurrency. To inspect the legitimacy of this claim, we compare the performance of the USD measured as the reciprocal of the U.S. Dollar Index (DX) for the same holding periods as those in each trading strategy. As shown in Table 5, the effect of the USD performance on the three cryptocurrencies is minimal, and each trading strategy still makes positive returns even after taking into consideration the fluctuation of the USD.

V. Conclusion

In this article, we examine investors' reactions to the major news announcements associated with the three largest cryptocurrencies: Bitcoin, Ethereum, and Ripple. Nonparametric tests including the rank test proposed by Corrado (1989) and the GRANK test proposed by Kolari and Pynnonen (2011) are applied as non-normality is found in the returns of these cryptocurrencies. High abnormal returns are observed on the event day (Day 0), indicating that

Table 5. Out-of-sample analysis: investment strategies on news events.

Price	14 February 2019	20 February 2019	HPR	25 March 2019	31 March 2019	HPR	18 June 2019	24 June 2019	HPR	Total Return
Bitcoin (BTC)	3588.72	3974.05		3924.55	4112.69		9280.54	11740.34		
Ether (ETH)	120.85	149.23		133.96	142.40		269.01	316.53		
Ripple (XRP)	0.30	0.33		0.30	0.31		0.44	0.47		
Investor A	Buy ETH	Sell ETH	7.44%	Buy ETH	Sell ETH	1.67%	Buy ETH	Sell ETH	24.61%	36.12%
$ 10,000.00	$ 9,850.00	$ 10,907.62	$ 744.01	$ 10,582.85	$ 11,090.18	$ 179.82	$ 10,923.83	$ 13,819.18	$2,688.06	$ 3,611.89
Investor B	Buy ETH	Sell ETH	19.81%	Buy ETH	Sell ETH	3.14%	Buy ETH	Sell ETH	15.90%	43.21%
$ 10,000.00	$ 9,850.00	$ 12,163.14	$1,980.69	$ 11,800.98	$ 12,544.49	$ 375.63	$ 12,356.32	$ 14,539.04	$1,964.63	$ 4,320.95
Investor C	Buy ETH	Sell ETH	7.16%	Buy ETH	Sell ETH	−0.25%	Buy ETH	Sell ETH	5.35%	12.61%
$ 10,000.00	$ 9,850.00	$ 10,879.10	$ 715.92	$ 10,555.18	$ 10,851.87	$ (26.83)	$ 10,689.09	$ 11,432.96	$ 572.37	$ 1,261.46
1/DX	0.01031	0.01037	0.55%	0.01036	0.01029	−0.63%	0.01024	0.01042	1.73%	1.65%
	11/13/2018	11/19/2018	HPR	6/27/2019	7/3/2019	HPR	7/10/2019	7/16/2019	HPR	Total Return
Bitcoin (BTC)	6339.17	4809.62		12355.06	11156.52		11343.12	9679.22		
Ether (ETH)	206.42	148.22		309.37	283.10		268.56	211.17		
Ripple (XRP)	0.51	0.48		0.42	0.39		0.33	0.31		
Investor D	Short sell BTC	Buy back BTC	24.15%	Short sell BTC	Buy back BTC	9.72%	Short sell BTC	Buy back BTC	14.69%	56.22%
$ 10,000.00	$ 9,850.00	$ 7,473.34	$2,414.56	$ 12,228.34	$ 11,042.10	$1,206.83	$ 13,417.08	$ 11,448.95	$2,000.71	$ 5,622.11
Investor E	Short sell BTC	Buy back BTC	28.21%	Short sell BTC	Buy back BTC	8.51%	Short sell BTC	Buy back BTC	21.39%	68.88%
$ 10,000.00	$ 9,850.00	$ 7,072.80	$2,821.11	$ 12,628.79	$ 11,556.43	$1,091.34	$ 13,703.76	$ 10,775.33	$2,975.49	$ 6,887.93
Investor F	Short sell BTC	Buy back BTC	6.76%	Short sell BTC	Buy back BTC	8.70%	Short sell BTC	Buy back BTC	5.74%	22.70%
$ 10,000.00	$ 9,850.00	$ 9,186.41	$ 675.79	$ 10,515.66	$ 9,603.41	$ 928.34	$ 11,430.07	$ 10,776.72	$ 665.76	$ 2,269.89
1/DX	0.01028	0.01040	1.15%	0.01039	0.01033	−0.57%	0.01030	0.01027	−0.31%	0.28%

Table 5 presents the holding period returns (HPR) as well as the total returns of six investment strategies that trade on news events that took place out of the sample period used in our baseline analysis. Each investor (strategy) invests $10,000 in either Bitcoin, Ethereum, or Ripple on the day that the news comes out (Day 0), and closes the position on Day 6, and repeats the same trade pattern two more times (total of three). *1/DX* indicates the reciprocal of the U.S. Dollar Index (DX).

there is a market reaction to major news events. Even three days before the event (Day −3), abnormal returns are detected in the same direction as the news (positive or negative). This may imply that the market reacts to rumours of upcoming events. In general, cumulative abnormal returns (CAR) diverge during the event windows of (−3, 6) and (0, 6), suggesting that the information is not fully reflected in prices immediately after the events. This also indicates that there is a positive trade opportunity for an investor who begins trading even after the news comes out during the period examined. The magnitudes of CARs are larger for negative events than for positive events, indicating that the market reaction to negative events is stronger than that to positive events.

The findings of this study have crucial implications for arbitragers, investors and practitioners. Progressive investment strategies in which investors take a position in the market on the day of a news announcement are found to make profits. In other words, it is not too late to join the market and gain positive profits even after the event becomes public information. This is not possible in a market where the current prices reflect all publicly available information.

While we present significant results in this article, data limitation has been a concern in our study. For example, we limited our analysis only on the three largest cryptocurrencies partially due to inadequate time series lengths and data unavailability of other cryptocurrencies. Also, the cryptocurrency market experienced extreme volatility, potentially classified as a market bubble, from the end of 2017 to the beginning of 2018, and it has been perceived to be a more volatile market than many other markets. Regime switching models for capturing changes in stock and interest rate behaviour (e.g. Hamilton 1989; Pagan and Sossounov 2003; Sims and Zha 2006; Ang and Timmermann 2011) as well as a jump process proposed by Cox and Ross (1976) and a jump diffusion process introduced by Merton (1976) could be applied to further study the nature of cryptocurrency returns. Another limitation lies in the conclusion drawn by the outcomes of the mean-adjusted returns model. A couple of newly launched indices such as Bloomberg Galaxy Crypto Index and CMC Crypto 200 Index could serve as dependable cryptocurrency market benchmarks once data becomes available. The long-term persistence of our findings must be re-evaluated, and longitudinal analysis can be possible only as longer periods of data become available. Other potential macro-factors such as the global monetary policy and the role of global risk factors could be examined in greater depth as well.

Acknowledgments

We would like to thank the Editor, Dr. David Peel, and anonymous referee for providing crucial suggestions and comments that improved the article substantially. We are also appreciative of the insightful comments from Ali M. Parhizgari, Qiang Kang, Özde Öztekin, and session participants at the 2019 Eastern Finance Association Annual Meeting and 2019 Southwestern Finance Association Annual Meeting. Remaining errors are ours.

Disclosure statement

No potential conflict of interest was reported by the authors.

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